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# Modelling momentum winner/loser asymmetry:

The sources of winner and loser returns in the ASX200 and S&P500

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## Abstract

There is an established body of work showing that the sources of momentum returns change over time. This paper finds that there is also winner/loser asymmetry - that the sources of the winner and loser components of momentum returns differ from each other at the same point in time. Together, these results raise concerns about the prospect of finding a single cause for momentum profits, as most efforts to date have tried to do. Rather, they indicate that investigation should proceed using time-varying, nonparametric and ensemble techniques.

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## 1. Introduction

"Buy low, sell high" is the common-sense maxim that causes the inexperienced trader to lose money on the stock market. To the general public, "buy low" means buy when prices have fallen, and "sell high" means sell when prices have risen. However, prices fall or rise for only one reason - because the market believes they are too high or too low. Thus the inexperienced trader does the opposite of what they should do - buying high and selling low - with inevitable results.

Correct interpretation of this common-sense maxim leads to buying when returns are high, even if prices are at their all-time high, and selling or short-selling when returns are low, even if prices are at their all-time low. This strategy, when combined with the construction of an equally-weighted zero-cost portfolio, is known as "momentum investing". First documented by Jegadeesh and Titman (1993), it works in most market conditions, and is at the heart of several trading techniques used for many years by both technical analysts (Dunham, 2011) and investment funds (Grinblatt, Titman, & Wermers, 1995).

Momentum investing relies on winner and loser persistence: the investor identifies the securities with the best and worst returns over the past few months – the winners and the losers – and bets that the winners will, on average, continue to outperform the losers over the next few months, regardless of the actual direction that either group takes. This strategy is typically actioned by sorting securities on recent return, and forming an equally-weighted zero-cost portfolio, shorting the lowest decile to purchase the highest decile. This Winners Minus Losers (WML) portfolio is held for a fixed period, and the repeating of this procedure each month yields a systematic profit, using only one return observation per stock per month to enter the market, and with a timed exit. Thus momentum investing is a successful strategy that involves minimal information, effort and up-front costs.

Momentum is considered anomalous in current market theories. Modern Portfolio Theory constructs optimal return-maximising risk-minimising portfolios, yet momentum profits using equally weighted portfolios and takes no account of risk. Arbitrage Pricing Theory (APT) assumes that prices move quickly to stable levels through trading, yet momentum assumes prices trend slowly. The weak form of the Efficient Market Hypothesis (EMH) states that it should be impossible to systematically profit based on no information but past prices, yet the typical execution of the momentum strategy profits from no information other than index membership and just two past price points per security. This is why momentum is labelled the "premier anomaly" (Fama & French, 2008).

While there are several risk-based and behavioural theories that attempt to explain the existence of the momentum anomaly, there is no compelling theory even after 25 years of study on over 200 years of market data (Asness, Frazzini, Israel, & Moskowitz, 2014). These timeframes also highlight the anomaly's persistence. According to APT and the EMH, an anomaly as well-known and widely-used (in one form or another) as momentum should result in it being "arbitraged away" – the profitable holding period should shrink and the profitability should reduce as momentum trading becomes widespread. Yet Vanstone and Hahn (2017) examined momentum with portfolio formation and holding periods from 3 to 24 months, showing that this has not happened.

It is clear that while the momentum anomaly is persistent it is not consistent, with widely varying profits (Antoniou, Lam, & Paudyal, 2007; Galariotis, 2010) and even short periods of significant losses (Barroso & Santa-Clara, 2015; Daniel & Moskowitz, 2013). The inconsistency has led several authors to posit that in any one market, several of the “competing” theories behind momentum are all more or less true at different times, depending on market conditions (Du & Watkins, 2007; Grundy & Martin, 2001).

Several authors have reasoned that momentum’s persistence is due not to risk-based or behavioural causes but to limitations on arbitrage. Jacobs (2015) investigated this possibility for 100 financial anomalies, including momentum and several of what he labelled “enhanced momentum” papers. While momentum sorts only by past returns, the enhanced momentum papers attempt to explain and improve on momentum’s performance by incorporating some additional piece of information into the sorting step (e.g. a dual-sort on past returns and one of price-to-book ratio, market capitalisation, number of analysts reporting on the security, volatility, 12-month high etc.). Each additional variable is meant to represent some underlying hypothesis about a possible explanation for momentum returns (e.g. firm value, firm size, information availability, risk, behaviour etc.).

Jacobs found little evidence to support the limitations-to-arbitrage thesis. However, a study of the enhanced momentum papers he used yields two interesting observations not discussed in those papers or by Jacobs.

The first stems from the fact that enhanced momentum portfolios are not momentum portfolios, having different constituents constructed via more complex ranking procedures incorporating extra information. The more complex sorting makes it unclear whether excess returns are due to momentum or to sources outside of it. Furthermore, this new information is often associated with some other well-defined market anomaly, making it unclear which anomaly is actually being studied. Additionally, while momentum is the exemplar weak-form EMH anomaly, several of the enhanced momentum papers incorporate semi-strong-form information. These concerns make it difficult to discern exactly what the enhanced momentum results say about the standard momentum anomaly.

The second observation is that several papers claimed their added sorting variable affected one side of the momentum trade, but not the other. That is, it has the effect of either increasing the return to buying winners only, or the return to short-selling losers only, but not both. This raises the possibility of winner/loser asymmetry; i.e. that returns to winners and losers may be asymmetrically affected by security properties, market factors, information availability, risk, behaviour etc. This calls into question the whole idea that the momentum anomaly yields to a single explanation – an assumption behind the majority of momentum papers. This assumption has already been questioned by Du and Watkins (2007), who show that the sources of momentum profits change over time. The general question at hand is whether there are multiple sources of momentum profits at any particular point in time, and the specific question is whether there are separate sources of profits from buying momentum winners and short-selling momentum losers.

The first contribution in this paper is to address the question of whether winner/loser asymmetry exists in standard momentum, in both the Australian and US markets. The sorting variables from the enhanced momentum papers, along with other variables representing market conditions, are used as explanatory variables in separate linear models for returns to winners and returns to losers. The winner and loser models are then compared by examining the differences in the importance, sign and magnitude of the coefficients, and by the models' explanatory power. The winner and loser models are found to contain a set of similar coefficients, and a set of dissimilar ones, indicating both symmetrical and asymmetrical components to the explanations for winner and loser returns. Additionally, the models for returns to losers are found to have greater explanatory power than the models for winners. These results imply that there are separate sources of profits from momentum winners and momentum losers during any particular period and, together with Du and Watkins (2007), that no current single theory or linear model can explain momentum returns.

The second contribution is the use of upper and lower semivariance in these models, both at the market and security levels. While several of the enhanced momentum papers use volatility as their additional ranking variable in order to investigate whether risk is a factor in momentum, none of these papers were specifically looking for winner/loser asymmetry. As winners (losers) suffer from downside (upside) risk but benefit from upside (downside) risk, dropping the assumption of symmetric variance is natural for this investigation, and the results clearly indicate that winner and loser returns have different exposures to each.

A third finding is that several of the enhanced momentum results were found to have little or no explanatory power for standard momentum winner and loser returns, indicating that at least some of the enhanced momentum results may be due to something other than momentum.

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## 2. Literature Review

### Standard Cross-Sectional Momentum

The seminal cross-sectional momentum paper is Jegadeesh and Titman (1993), but the WML method used dates back to Beaver and Landsman (1981). They described the construction of two equally weighted portfolios – the winners and losers – based purely on immediate past residual return, and observed some systematic residual behavior, manifesting itself in a positive WML return associated with certain events such as earnings announcements. De Bondt and Thaler (1985, 1987) adapted the procedure and identified the Long-Term Reversion anomaly – returns to winner (loser) portfolios that fall (rise) over timescales larger than a year. They exploited the phenomenon by shorting the winner portfolio to partially fund the loser portfolio. They also introduced the “J/K” terminology in common use with this methodology, with J standing for the number of immediate past months – the formation period - over which to calculate past return, and K standing for the number of future months – the holding period - over which to hold the constructed portfolio.

Jegadeesh and Titman (1993) reduced the timescale and used a zero-cost strategy, shorting the losers to fund the winners. They found that returns to winner (loser) portfolios rise (fall) over several months, and thus identified and defined the cross-sectional momentum anomaly. The canonical version of their method is as follows. A set of liquid securities is ranked by their recent J-month returns, and divided into deciles. The highest and lowest deciles of return are labelled “winners” and “losers”, and the intervening deciles are ignored. A zero-cost equally-weighted WML portfolio is constructed by shorting the losers to purchase the winners. The portfolio is closed out after a holding period of K months. This procedure is typically repeated each month, forming a staggered series of overlapping portfolios, yielding abnormal returns. They performed experiments with values for J and K ranging from 3 to 12 months, using NYSE and AMEX data from 1965 to 1989. Analysis was performed for  $J = K = 6$ , which yielded an average compounded excess return of 12.01% per year.  $J = K = 6$  remains the typical parameterization for momentum investigations in the literature.

As a result of the persistence of momentum’s anomalous behaviour, Carhart (1997) supplemented the three-factor model of Fama and French (1993) with a 12-month past returns factor (i.e. a momentum factor with  $J = 12$ ), stating “I employ the model to ‘explain’ returns, and leave risk interpretations to the reader” (Carhart, 1997, p. 61). The momentum factor has since been reviewed positively in Fama and French (2012) and Asness et al. (2014); it appears frequently in the factor model literature, and both the three and four factor models are now academically mainstream (Dempsey, 2013). However, being an empirical factor, it does not explain momentum; rather it attempts to measure it, leaving the explanation open as mentioned by Carhart. This is true of all empirical factors, as detailed mathematically by Smith and Walsh (2013) regarding empirical factors in finance specifically, and more philosophically by McMullin (1968) regarding empirical factors in general. The question of what theory or theories actually explains momentum thus remains open – a fact that Asness et al. (2014) note is one of several “myths” erroneously used as an argument to dismiss it as nothing more than a “hot potato” strategy.

### Australian WML and Momentum Studies

Following on from Beaver and Landsman (1981) and De Bondt and Thaler (1985, 1987), the WML methodology was employed to investigate the long-term reversion anomaly in Australia by Brailsford (1992) and Allen and Prince (1995). Both Australian studies reported an asymmetric result consistent with the US result of De Bondt and Thaler (1985), that price reversal was apparent for winners but not losers.

Using the ASX Approved Securities list, positive results were reported for the standard momentum strategy by Hurn and Pavlov (2003) and Demir, Muthuswamy, and Walter (2004); and for variants of the strategy by Marshall and Cahan (2005), and Bettman, Maher, and Sault (2009). Using the ASX200 members, positive results were reported for standard momentum by Galariotis (2010), who also lowered transaction costs and removed effects of data resampling by creating non-overlapping portfolios every J months, rather than the standard method of creating overlapping portfolios every month. Schneider and Gaunt (2012) find evidence for both price and earnings momentum, using data from the Australian Graduate School of Management Centre for Research and Finance.

Again using the ASX200 members, positive results were reported by Vanstone, Hahn, and Finnie (2012) and Vanstone and Hahn (2013), who showed that momentum in Australia recovered after the Global Financial Crisis, and who tabulated results demonstrating both the long-term reversion anomaly and momentum anomaly occurring in the same data set for different values of J and K. Vanstone and Hahn (2017) went on to find at least \$1.5 billion in momentum-based funds under management in Australia, showing that momentum in Australia is far from being of purely academic interest.

### Time Varying Characteristics of Momentum

There are many papers documenting the time-varying nature of the momentum anomaly. Hon and Tonks (2003) find that momentum is only apparent in certain time periods in the UK stock market. Antoniou et al. (2007) find that momentum profits vary systematically with business cycles. Galariotis (2010) finds that momentum results are positive but varying over time in the Australian market. Daniel and Moskowitz (2013) find that momentum yields strings of negative returns in high-volatility market “panic” states following market declines, though as pointed out by Asness et al. (2014), this is true of any factor. Barroso and Santa-Clara (2015) find that the risk associated with momentum varies significantly and predictably over time, and use this to propose a risk-adjusted momentum strategy.

While the above papers focus on the time-varying nature of momentum profits, others focus on the time-varying sources of those profits. Grundy and Martin (2001) show that the WML method guarantees time-varying factor exposure, as the factors themselves may not exhibit momentum-like behaviour. Du and Watkins (2007) find the sources of momentum profits to be time-varying also, and point out that this is a significant problem for current explanations for momentum which assume the sources are stable. They decompose the sources into behavioural, lead-lag and risk factors, divide their data into 3 equally-sized time periods, and show that behaviour is the dominant factor in the first period, but lead-lag effects are dominant in the second and third periods.

Further papers discussing the time-varying nature of momentum can be found in the literature review section of Vanstone and Hahn (2017).

### Enhanced Momentum

In a paper seeking to determine whether market anomalies were more influenced by market sentiment or the limits of arbitrage, Jacobs (2015) reviewed and tested 100 different market anomalies, including the original Jegadeesh and Titman momentum paper, and 15 enhanced momentum papers. Jacobs lists a set of 16 variables that these 15 enhanced momentum papers incorporate into the ranking step of their portfolio creation.

In the source papers, ranking on the new variable sometimes occurred before ranking on past return, sometimes after, and sometimes in place of. To unify his results, Jacobs retested each result, using a uniform procedure which involved ranking both variables independently, then combining those ranks as appropriate (usually by multiplying them) for each anomaly. In doing so, he showed that the efficacy of each introduced variable is not somehow dependent on their original ranking procedures, but is inherent in the variable itself.

Each source paper investigated some hypothesis to explain momentum's abnormal return. However, many of the papers used several variables to proxy for that hypothesis, and several variables appear in different papers proxying for different hypotheses. This renders grouping the variables by original hypothesis impossible. We instead group variables by their EMH information content. The first group are those variables constructed purely from past price information and representing weak-form EMH information, starting with the simplest – momentum itself, and the previous 52-week high or low – and ending with volatility. Volatility is variously associated with risk or information availability in the enhanced momentum literature, but as it is calculated using only past prices we include it here. The second group of variables incorporate transaction volume information. This information, like prices, is both public and directly related to actual trades, so it is perhaps arguable that this should also be considered weak-form EMH information. However, it takes more effort to access and is used far less frequently. The third group representing information availability is a little different, as these variables are trying to proxy for the availability or reliability of the above information. The fourth group of variables represent semi-strong-form EMH information. None of the source papers or Jacobs discussed the use of private strong-form EMH information.

The enhanced momentum variables, and the papers in Jacobs that employ them, are tabulated below, followed by a more detailed review of the papers associated with each variable.



*Table 1: Enhanced Momentum Papers in Jacobs (2015)*

Factor	References	Variable Group
Immediate Past Returns	Jegadeesh and Titman (1993)	Price-Based Variables...
Intermediate Past Returns	Novy-Marx (2012)	
Nearness to 52-Week High or Low	George and Hwang (2004)	
Extremity of Formation Period Returns	Bandarchuk and Hilscher (2013)	
Formation Period Return Consistency	Grinblatt and Moskowitz (2004)	
Information Discreteness	Da, Gurun, and Warachka (2014)	
Volatility	Jiang, Lee, and Zhang (2005) Zhang (2006)	... including risk
Continuing Overreaction	Byun, Lim, and Yun (2014)	Volume-Based Variables
Turnover Ratio	Lee and Swaminathan (2000)	
Market Capitalization	Hong, Lim, and Stein (2000) Zhang (2006)	Information Availability Variables
Firm Age	Jiang et al. (2005) Zhang (2006)	
Analyst Coverage	Hong et al. (2000)	
Analyst Forecast Dispersion	Zhang (2006)	
Credit Rating	Avramov, Chordia, Jostova, and Philipov (2007)	Semi-Strong form EMH Variables
Breadth of Ownership	Chen, Hong, and Stein (2002)	
Book to Price Ratio	Asness (1997)	
R <sup>2</sup>	Hou, Xiong, and Peng (2006)	

## Price-Based Variables

### *Immediate Past Returns*

Jegadeesh and Titman (1993) examine US return data from 1965 to 1989 and achieved a compounded excess return of 1% per month with a formation period of 6 months and a holding period of 6 months. This represents the standard momentum configuration cited in most of the momentum literature.

### *Intermediate Past Returns*

The simplest variation on this is by Novy-Marx (2012), who reports a 1.2% per month return using a holding period stretching from 12-months ago to 6 months ago, based on US data from 1926 to 2010. Novy-Marx claims that this form of the momentum anomaly supersedes the information reliability and return consistency explanations of Hong et al. (2000) and Grinblatt and Moskowitz (2004).

### *Nearness to 50-Week High or Low*

Another simple variation is by George and Hwang (2004), who rank on the ratio of the current price to the 52-week high instead of past return, also reporting just over 1.2% per month using US data from 1963-2001. They claim that their result supersedes the volume study of Lee and Swaminathan (2000). They also report an asymmetric result, in that no similar success was achieved using the ratio of the current price to the 52-week low. (Note that both ratios were tested in the current study).

### *Extremity of Formation-Period Returns*

Both of the previous enhanced momentum papers simply replace momentum's ranking variable with an alternative. With the following exception, the remaining papers use various forms of 2-variable ranking, with the standard momentum formation-period return plus an additional variable. Typically, the new procedure involves filtering first by past return, then ranking on the new variables to form winner and loser portfolios, or filtering first by the new variable, then ranking on past return to form portfolios. The claim of Bandarchuk and Hilscher (2013) is that these dual-sorting procedures work by selecting stocks with extreme past returns, and that this fully accounts for the results seen in many of the papers examined by Jacobs, notably Asness (1997), Daniel and Titman (1999), Lee and Swaminathan (2000), Hong et al. (2000), Zhang (2006), and Hou et al. (2006).

### *Formation-Period Return Consistency*

Grinblatt and Moskowitz (2004) examine US data from 1963 to 1999 and report an asymmetrical finding: that consistency of positive returns is important for predicting future positive returns, but consistency of past negative returns is irrelevant for predicting future negative returns. This is somewhat similar to the asymmetry reported by George and Hwang (2004). They also claim return consistency is more important than the information reliability and volume effects noted by Hong et al. (2000) and Lee and Swaminathan (2000) respectively.

### *Information Discreteness*

Da et al. (2014) use daily price direction information (ignoring magnitude) over the formation period, and the monthly compounded return over 12 months, to create a measure of the information discreteness (ID). Using US data from 1927 to 1992, they find that profits to momentum decrease (from a high of about 1% per month) with decreasing continuity of information arrival, claiming their "frog in the pan" hypothesis supersedes Lee and Swaminathan (2000), Daniel and Titman (1999), Hong et al. (2000), George and Hwang (2004), Grinblatt and Moskowitz (2004), and Zhang (2006).

### *Volatility*

Jiang et al. (2005) and Zhang (2006) use volatility as proxy for information uncertainty, though most literature outside the enhanced momentum set considers volatility as a proxy for risk. Both find that momentum returns improve with increased volatility. In particular, Jiang et al. find that higher volatility results in lower future returns on average, but higher returns for momentum, using US data from 1965 to 2001, and countering the claims of Asness (1997) and Lee and Swaminathan (2000).

## Volume-Based Variables

### *Continuing Overreaction*

Byun et al. (2014) construct a continuing overreaction (CO) measurement, with the signs of the data points taken from returns but the magnitudes from volume traded. Using US data from 1965 to 2009, they find that ranking on this yields good predictive value for both losers and winners.

### *Turnover Ratio*

Sorting first on returns then by turnover ratio (TR) using US data from 1965 to 1995, Lee and Swaminathan (2000) report 1.08% monthly returns, and the asymmetric result that extreme winners have a higher transaction ratio than extreme losers.

The turnover ratio is one of two variables that incorporates the number of shares outstanding. This is not weak-form EMH information, being available only from company announcements and containing information about stock splits, merges, issuances etc. However, its' use here is as a scaling factor for volume of stocks traded, rather than as an additional information source. Similarly, its use in the market capitalisation variable below is as a proxy for size rather than company news. As market capitalisation is also calculated using the last closing price of the formation period, it is highly correlated with formation period return, and we therefore consider it as a weak-form variable.

## Information Availability Variables

### *Market Capitalisation*

Hong et al. (2000) and Zhang (2006) both use market capitalisation as one of their proxies for information availability and certainty. Hong et al. examine US data from 1976 to 1996, Zhang from 1983 to 2001. Both detect a small firm effect - that momentum works better for smaller firms than larger ones. Both interpret this in terms of information about smaller firms being less available and less certain than information about larger firms. Hong et al. do not reference any enhanced momentum papers from the Jacobs set. Zhang positively references Hong et al., and claims that the information certainty hypothesis supersedes Daniel and Titman (1999) and Lee and Swaminathan (2000).

### *Firm Age*

Jiang et al. (2005) and Zhang (2006) use firm age as a proxy for information uncertainty. Both find that momentum returns diminish with increasing firm age.

### *Analyst Coverage and Analyst Forecast Dispersion*

Hong et al. (2000) and Zhang (2006) also use analyst coverage (the number of analysts reporting on a security) and analyst dispersion (the difference of opinion of analysts on a security) respectively, as measures of information availability and uncertainty. Hong et al. find momentum works best for firms with low analyst coverage, with the effect being larger for past losers than for past winners.

## Semi-Strong Form EMH Variables

### *Credit Rating*

Using US data from 1985 to 2003, Avramov et al. (2007) find momentum strongest in firms with low credit rating, and non-existent in firms with high rating, claiming that a small number of poor firms account for a large proportion of momentum returns, and that this result supersedes all of the information availability variables and papers mentioned above.

### *Breadth of Ownership*

Chen et al. (2002) rank stocks on change in breadth of mutual fund ownership, using US data from 1979 to 1998. They find winner minus loser returns of over 6%, reduced to 4.95% when controlling for momentum and other factors.

### *Book to Price Ratio*

Using book-to-price ratio as the measure of value over US data from 1963 to 1994, Asness (1997) reported that value investing is enhanced if you first filter for momentum losers, and momentum investing is enhanced if you first filter for overpriced securities.

### *R<sup>2</sup>*

Hou et al. (2006) set out to show that  $R^2$  is a measure of how well investors process information, rather than the more usual interpretation in the momentum literature as a measure of the market's information efficiency. They use momentum returns from 1963 to 2002 as a proxy for investor overreaction, and find a negative relationship between  $R^2$  on a model on fundamental data and momentum return.

## Australian Enhanced Momentum Studies

A number of papers have been written that confirm these enhanced momentum findings in an Australian context. The aforementioned paper by Marshall and Cahan (2005) confirms the 52-week high finding of George and Hwang (2004). Hurn and Pavlov (2008) employ a similar size-based dual-sort procedure to Hong et al. (2000) and Zhang (2006) with similar results. Aharoni, Ho, and Zeng (2012) employ dual sorting based on both volatility and book-to-price, and report similar findings to Jiang et al. (2005) and Zhang (2006) for volatility and Asness (1997) for book-to-price. Brailsford and O'Brien (2008) and O'Brien, Brailsford, and Gaunt (2010) conduct double- and triple-sorting respectively, to identify the relationships between the size, value and momentum. Their findings are again similar to Hong et al. (2000) and Zhang (2006) regarding size, and Asness (1997) regarding value, with the additional asymmetric finding that the size effect is more marked in losers than winners. In a larger study covering six anomalies, Dou, Gallagher, and Schneider (2013) find results consistent with Brailsford and O'Brien (2008), with the addition that momentum returns are negative for micro-cap stocks. Additionally, Chan and Docherty (2016) find strong evidence of style momentum in the Australian market, using portfolios double-sorted on size and book to market ratio.

## Semivariance

Markowitz (1959) used the term “semi-variance” to denote downside risk, and devoted a chapter to its definition, comparison to variance, geometric analysis, and calculation. In particular, he notes that variance is superior in terms of “cost, convenience, and familiarity”, but that variance considers extremely low and extremely high returns as equally undesirable, and that portfolios constructed using semivariance are superior in this regard (p.193). Sortino and Satchell (2001) give an overview of the theory and applications of semivariance in financial markets. Bond and Satchell discuss the use of semivariance in foreign exchange markets, finding mature markets to be far more symmetric than emerging markets (Bond & Satchell, 2002, 2006a, 2006b).

While papers citing the use of semivariance in momentum studies are difficult to find, Post, Vliet, and Lansdorp (2009) is relevant to enhanced momentum in that it uses downside risk as a sorting factor for portfolio selection, finding it to have explanatory power over stock characteristics including the momentum factor. No mention is made of upside risk – which is not surprising, as upside is not considered a risk per se outside the context of shorting. However, Farinelli and Tibiletti (2008) create an index for ranking assets using both downside and upside moments.

### Specific Asymmetry Findings

Several of the momentum and enhanced momentum studies above reported various kinds of asymmetry, specifically:

1. George and Hwang (2004) report success when ranking on the 52-week high, but not on the 52-week low;
2. Grinblatt and Moskowitz (2004) report that consistency of positive returns is important for predicting future positive returns, but consistency of past negative returns is irrelevant for predicting future negative returns;
3. Lee and Swaminathan (2000) report that extreme winners have a higher transaction ratio than extreme losers;
4. Hong et al. (2000) find momentum works best for firms with low analyst coverage, with the effect being larger for past losers than for past winners;
5. Brailsford and O'Brien (2008) and O'Brien, Brailsford, and Gaunt (2010) report that the size effect is more marked in losers than winners.

Independently, none of these findings is necessarily remarkable. Collectively, they indicate the possibility that winner returns are more dependent on weak-form EMH information than loser returns (from results 1-3), whereas loser returns are more dependent on information availability than winner returns (from results 3-5). Additionally, the observation was made that upside and downside risk would have opposite effects on the profitability of long winners and short losers, implying that asymmetrical risk would affect momentum profitability, but that all of the above studies either assumed symmetrical risk or did not take risk into account. These collective findings formed the impetus for the current study of winner/loser asymmetry.

### 3. Methodology

The momentum literature shows that the cross-sectional momentum anomaly is persistent but inconsistent, with momentum profits and the sources of those profits varying over time and with market states. The enhanced momentum literature hints at the possibility that the sources of winner returns may be different from the sources of loser returns. However, as enhanced momentum portfolios differ from momentum portfolios, we cannot assume that this possible asymmetry applies to momentum.

To see if it does, (i.e. to test the hypothesis that standard momentum winner and loser portfolios have different sources of returns), we construct momentum winner and loser portfolios normally and model their returns separately. To include the information that originally lead us to this hypothesis, we include several variables used for enhanced momentum portfolio construction from the papers studied by Jacobs (2015) in our set of candidate regressors. To cater for the logic of Grundy and Martin (2001), that winners and losers are likely to have different exposures to the same market factors, we also include several market-factor variables in our candidate regressor set<sup>1</sup>. To cater for our observation that winner and loser portfolios benefit and suffer from upside and downside risk in opposite ways, we use upper and lower semivariance in place of variance in our candidate regressor set. To cater for the time-varying aspect of momentum, we divide our time period into 3 equal periods as per Du and Watkins (2007)<sup>2</sup>. We then use the Bayesian Information Criterion (BIC)<sup>3</sup> to select six parsimonious models – a winner and loser model for each period. Finally, we compare the winner and loser model in each period for factor inclusion, for coefficient sign, magnitude and significance, and for whether each included factor represents past prices, upside or downside risk, past volumes, information availability, semi-strong EMH information, or market state.

This procedure was performed for the S&P/ASX200 and the S&P500.

#### Data

Data was collected from Bloomberg L.P. (2016) for the S&P/ASX200 and the S&P500 indexes and their constituents, from March 1999 (12 months prior to the S&P/ASX200 index going

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<sup>1</sup> For our own situation, we use the following reasoning. At any one time, the momentum winners portfolio can be in a rising, neutral, or falling state, and likewise the losers portfolio. Thus, there are 9 possible combinations or winner/loser portfolio states, only 3 of which have winners and losers in the same state. Following on from the logic of Grundy and Martin (2001), we reason that returns to winners and losers must at least have different market-state exposures from each other for much of the time. We thus include market variables in our separate models for winners and losers portfolios.

<sup>2</sup> General support for this approach comes from the seminal Chatfield (1995). When discussing an alternative to using a weighted linear combination of time-series models, Chatfield suggested to “use different models to describe different parts of the data, rather than to pretend that a single model can describe all the data. This applies particularly to time series analysis where the properties of the most recent data may differ markedly from those of earlier data and a global model fitted to all the data may give poor predictions” (p.429).

<sup>3</sup> The BIC is used to keep the models small in the spirit of Harvey, Liu, and Zhu (2016), who advocate setting a higher-than-normal bar for variable inclusion when creating models to explain the cross-section of returns. The BIC yields smaller models than the Akaike Information Criterion (AIC) due to its higher penalty for variable inclusion (Chakrabarti & Ghosh, 2011).

live) to January 2016. The Australian market was chosen as one where the existence of both standard and enhanced momentum have been clearly demonstrated both pre- and post- GFC, and where standard momentum is used in industry (Vanstone & Hahn, 2017). Unlike the majority of US-based papers listed, which excluded closed-end funds, REITs and American Depositary Receipts, the current equity-based study uses the constituents of the S&P/ASX200 and the S&P500, and includes equities of all industry classifications.

Returns for each month were then ranked by past 6-month return and divided into deciles, as per the standard momentum procedure of Jegadeesh and Titman (1993). However, instead of subtracting loser returns from winner returns and reporting on the resulting return, separate 6-month future return regression models for were constructed for winner and loser returns, using as factors the enhanced momentum ranking variables from Jacobs, for which sufficient data was available in Bloomberg.

*Table 2: Bloomberg fields used for factor construction*

Factor	Bloomberg Fields Used
Immediate Past Returns	<b>Past price or past return fields:</b> DAY_TO_DAY_TOT_RETURN_GROSS_DVDS PX_LAST INTERVAL_LOW INTERVAL_HIGH
Intermediate Past Returns	
Nearness to 52-Week High or Low	
Extremity of Formation Period Returns	
Formation Period Return Consistency	
Information Discreteness	
Volatility	<b>Volume fields:</b> PX_VOLUME BS_SH_OUT EQY_SH_OUT
Continuing Overreaction	
Turnover Ratio	
Market Capitalization	DATE_OR_YEAR_OF_INCORPORATION OFFERING_PRELIM_FILING_DT OFFERING_FIRST_LISTING_DATE EQY_INIT_PO_DT
Firm Age	
Analyst Coverage	
Analyst Forecast Dispersion	
Credit Rating	Historical data not available in Bloomberg
Breadth of Ownership	
Book to Price Ratio	PX_TO_BOOK_RATIO
R <sup>2</sup>	COEF_DETER_R_SQUARED

Variable names and construction formulae are shown below. Where practical, the variable names from the source papers were used.



Table 3: Factor variables and construction formulae

Factor	Source Variable or Formula
Immediate Past Returns	$R_{j6}$ : the 6-month past return minus the risk-free rate. The 1-year risk-free rate was used for the ASX200, and the 6-month rate for the S&P500, as these rates had the best data availability in Bloomberg.
Intermediate Past Returns	$R_{j12-6}$ : the return from the 6-months prior to $R_{j6}$
Nearness to 52-Week High or Low	High and Low Ratios: $HR = \frac{ClosingPrice}{52WeekHigh}$ , $LR = \frac{52WeekLow}{ClosingPrice}$
Extremity of Formation Period Returns	Momentum Strength: $MS = e^{ \log(1+R_{j6}) - \log(1+R_{median,6}) } - 1$ where $R_{median,6}$ is the median of monthly returns for the past 6 months
Formation Period Return Consistency	(Historical data not extracted at time of writing)
Information Discreteness	$ID = sign(R_{j12}) * (\%neg - \%pos)$ where $R_{j12}$ is the 12-month past return; $\%neg, \%pos$ are the percentage of down and up days.
Volatility	$uppersem = \frac{1}{n} \sum_{r > \mu} (r - \mu)^2$ $lowersem = \frac{1}{n} \sum_{r < \mu} (r - \mu)^2$ where $r = \log(1 + R_{j6,daily})$ and $R_{j6,daily}$ is the daily return for the past 6 months
and Continuing Overreaction	$CO = \frac{\sum WeightedSignedVolumes}{MeanVolume}$ where $WeightedSignedVolumes$ are the monthly signed volumes (i.e. the monthly volume, positive or negative if the monthly return was positive or negative), multiplied by a scaling factor, for the past 12 months; $MeanVolume$ is the mean monthly volume for the past 12 months.
Turnover Ratio	$TR = \frac{Volume}{SharesOutstanding}$
Market Capitalization	$MCap = SharesOutstanding * ClosingPrice$
Firm Age	$FirmAge$ : in years
Analyst Coverage	$TotAnalystsRec$ : Monthly number of analysts recorded advising on the security
Analyst Forecast Dispersion	
Credit Rating	(Historical data not available in Bloomberg)
Breadth of Ownership	
Book to Price Ratio	$PxToBookRatio$
$R^2$	$R^2$ : The coefficient of determination for the security's beta over the past 6 months



Transformations were then applied, which consisted of winsorising the accounting variables (the number of shares outstanding, and *PxToBookRatio*), taking the square root of  $R^2$ , dividing *TR* by 100,000, and taking the log to base 10 of *MCap*, *FirmAge*, *PxToBookRatio*,  $R_{j12-6} + 1$ , and *MS*. Note that as the source papers used these variables for ranking rather than regression, they offered no guidance regarding transformations. We decided to winsorise only the accounting variables and not market data, due to the nature of the WML methodology which specifically includes the extreme decile returns while excluding the 80% of the central distribution.

## Models

Models are of the form:

$$\begin{aligned}
 R_{portfolio} &= EMV + MV \\
 &= (PV + RV + VV + IAV + SSV) + MV \\
 &= \beta_0 + [\beta_1 R_{j6} + \beta_2 \log(R_{j12-6}) + \beta_3 HR + \beta_4 LR + \beta_5 \log(MS) + \beta_6 ID] \\
 &\quad + [\beta_7 lowersem + \beta_8 uppersem] + [\beta_9 CO + \beta_{10} TR] \\
 &\quad + [\beta_{11} \log(MCap) \\
 &\quad + \beta_{12} \log(FirmAge) + \beta_{13} TotAnalystRec] + [\beta_{14} \log(BookToPxRatio) \\
 &\quad + \beta_{15} \sqrt{R^2}] + [6R_{j6,market} + \beta_{17} lowersem_{market} \\
 &\quad + \beta_{18} uppersem_{market} + \beta_{19} \log(BookToPxRatio_{market})] + \varepsilon
 \end{aligned}$$

*EMV* = Enhanced Momentum Variables

*MV* = Market Variables

*PV* = Price Based Variables

*RV* = Risk Based Variables

*VV* = Volume Based Variables

*IAV* = Information Availability Variables

*SSV* = Semi Strong EMH Variables

For stepwise regression, the above model was used as the full model, with the base model representing standard momentum:

$$R_{momentum} = \beta_0 + \beta_1 R_{j6} + \varepsilon$$

## Results

### Models

The winner and loser models for each period are shown below, for the ASX200 and the S&P500. The table below each pair of models shows the number of regressors in each model categorised by regressor types discussed above, with each model containing up to 6 price regressors, 2 risk regressors, 2 volume regressors, 3 information availability regressors, 2 semi-strong EMH regressors and 4 market factor regressors. In the discussions that follow, it must be remembered that anything which positively (negatively) affects returns is beneficial

(detrimental) for the winners portfolio which is held long, and detrimental (beneficial) for the losers portfolio which is held short.

ASX200, Period 1 (April 2000 – May 2005)

$$\begin{aligned}
 R_{winners} &= 0.841 - 706.lowersem + 295.uppersem - 0.0892.log(MCap) \\
 &\quad + 0.012.TotAnalystRec - 0.75.R_{j6,market} \\
 &\quad + 1.321.log(BookToPxRatio_{market}) + \varepsilon \\
 R_{losers} &= 1.177 + 0.843.PR - 0.0288.CO - 0.177.log(MCap) + 0.249.log(FirmAge) \\
 &\quad + 0.195.log(BookToPxRatio) + 0.959.R_{j6,market} \\
 &\quad + 3.385.log(BookToPxRatio_{market}) + \varepsilon
 \end{aligned}$$

Table 4: Regressor counts for ASX200 Period 1

	Winners	Losers
Price	0 / 6	2 / 6
Risk	2 / 2	0 / 2
Volume	0 / 2	0 / 2
Information Availability	2 / 3	2 / 3
Semi-Strong EMH	0 / 2	1 / 2
Market Factors	2 / 4	2 / 4

$R^2$  is 0.10 for winners and 0.26 for losers, so loser returns are considerably better accounted for. Returns to winners are explained by risk, information availability and market factors, whereas returns to losers are explained by past price and volume, information availability, value and market factors. Winners are exposed asymmetrically to downside and upside risk, whereas losers are not significantly exposed to either. Winners benefit from information availability whereas losers suffer from it. Losers are more affected than winners by past market returns and market value.

ASX200, Period 2 (June 2005 – June 2010)

$$\begin{aligned}
 R_{winners} &= 0.44 - 0.195.log(R_{j6-12}) - 0.106.log(MCap) + 0.898.R_{j6,market} \\
 &\quad + 20220.lowersem_{market} - 23620.uppersem_{market} + \varepsilon \\
 R_{losers} &= 1.281 + 0.406.log(R_{j6-12}) + 0.42.log(MS) + 76.5.uppersem \\
 &\quad - 0.263.log(MCap) + 0.0195.TotAnalystRec + 1.481.R_{j6,market} \\
 &\quad + 14140.lowersem_{market} - 12560.uppersem_{market} \\
 &\quad + 2.544.log(BookToPxRatio_{market}) + \varepsilon
 \end{aligned}$$

Table 5: Regressor counts for ASX200 Period 2

	Winners	Losers
Price	1 / 6	2 / 6
Risk	0 / 2	1 / 2
Volume	0 / 2	0 / 2
Information Availability	1 / 3	2 / 3
Semi-Strong EMH	0 / 2	0 / 2
Market Factors	3 / 4	4 / 4

$R^2$  is 0.17 for winners and 0.5 for losers, so loser returns are again considerably better accounted for. Returns to winners and losers are explained by past prices, information availability and in a large part by market factors which dominate during the Global Financial Crisis. Shadow momentum indicates price reversal for winners but not for losers. Losers are also exposed to upside risk, but gain no significant benefit from downside risk.

ASX200, Period 3 (July 2010 – July 2015)

$$\begin{aligned}
 R_{winners} &= 0.0717 + 0.361.\log(R_{j6-12}) - 329.lowersem + \varepsilon \\
 R_{losers} &= 0.504 + 113.lowersem - 310.uppersem \\
 &\quad + 2.083.\log(BookToPxRatio_{market}) + \varepsilon
 \end{aligned}$$

Table 6: Regressor counts for ASX200 Period 3

	Winners	Losers
Price	1 / 6	0 / 6
Risk	1 / 2	2 / 2
Volume	0 / 2	0 / 2
Information Availability	0 / 3	0 / 3
Semi-Strong EMH	0 / 2	0 / 2
Market Factors	0 / 4	1 / 4

$R^2$  is 0.08 for both winners and losers, so explanatory power of the models is poor post GFC. Both winners and losers suffer from downside risk in this period, with downside risk indicating an unwanted rise in returns for losers.

S&P500, Period 1 (April 2000 – May 2005)

$$\begin{aligned}
 R_{winners} &= 1.116 - 102.lowersem - 0.0546.\log(TR) - 0.085.\log(MCap) \\
 &\quad + 0.049.\log(BookToPxRatio) - 0.159.sqrt(R^2) + 0.557.R_{j6,market} \\
 &\quad - 6213.lowersem_{market} + 9001.uppersem_{market} \\
 &\quad + 1.011.\log(BookToPxRatio_{market}) + \varepsilon \\
 R_{losers} &= 1.465 + 0.46.R_{j6} - 0.449.PR + 149.lowersem - 105.uppersem \\
 &\quad - 0.127.\log(TR) - 0.223.\log(MCap) + 0.0875.\log(FirmAge) \\
 &\quad + 0.00316.TotAnalystRec - 4436.lowersem_{market} \\
 &\quad + 5258.uppersem_{market} + \varepsilon
 \end{aligned}$$

Table 7: Regressor counts for S&P500 Period 1

	Winners	Losers
Price	0 / 6	2 / 6
Risk	1 / 2	2 / 2
Volume	1 / 2	1 / 2
Information Availability	1 / 3	3 / 3
Semi-Strong EMH	2 / 2	1 / 2
Market Factors	4 / 4	2 / 4

$R^2$  is 0.21 for winners and 0.17 for losers. Returns to winners are explained by downside risk, volume, information availability, semi-strong information and market factors, while returns to losers are explained by past prices, downside and upside risk, several information availability variables, and market risk.

S&P500, Period 2 (June 2005 – June 2010)

$$\begin{aligned}
 R_{winners} &= 0.28 - 0.06.R_{j6} - 0.327.R_{j6-12} - 0.1.\log(MCap) + 0.00291.TotAnalystRec \\
 &\quad + 0.241.sqrt(R^2) + \varepsilon \\
 R_{losers} &= 1.083 - 0.238.R_{j6} + 0.571.R_{j6-12} - 1.032.PR + 145.uppersem \\
 &\quad - 0.254.\log(MCap) + 0.00815.TotAnalystRec \\
 &\quad - 0.138.\log(BookToPxRatio) + 0.132.sqrt(R^2) + 1.049.R_{j6,market} \\
 &\quad - 3205.lowersem_{market} + 5230.uppersem_{market} \\
 &\quad + 1.407.\log(BookToPxRatio_{market}) + \varepsilon
 \end{aligned}$$

Table 8: Regressor counts for S&P500 Period 2

	Winners	Losers
Price	2 / 6	3 / 6
Risk	0 / 2	1 / 2
Volume	0 / 2	0 / 2
Information Availability	2 / 3	2 / 3
Semi-Strong EMH	1 / 2	2 / 2
Market Factors	0 / 4	4 / 4

$R^2$  is 0.18 for winners and 0.46 for losers, so again losers are better accounted for. Winners show a reversal for both momentum and shadow momentum, this likely being due to the Global Financial Crisis. Losers show a reversal for both momentum and price ratio, and a strong correlation to the market.

S&P500, Period 3 (July 2010 – July 2015)

$$\begin{aligned}
 R_{winners} &= 0.075 + 0.348.R_{j6} - 0.384.\log(MS) - 0.81.R_{j6,market} \\
 &\quad + 0.644.\log(BookToPxRatio_{market}) + \varepsilon \\
 R_{losers} &= 1.461 - 3165.uppersem_{market} + 3.501.\log(BookToPxRatio_{market}) + \varepsilon
 \end{aligned}$$

Table 9: Regressor counts for S&P500 Period 3

	Winners	Losers
Price	2 / 6	0 / 6
Risk	0 / 2	0 / 2
Volume	0 / 2	0 / 2
Information Availability	0 / 3	0 / 3
Semi-Strong EMH	0 / 2	0 / 2
Market Factors	2 / 4	2 / 4

$R^2$  is 0.08 for winners and 0.25 for losers, so losers are better accounted for, and in this case the explanation involves only market factors.

## Discussion

The models indicate the following stylised results.

1. Some specific sources of momentum winner and loser returns appear relatively stable across time and between winner and loser models. However:
2. In general, the sources of momentum winner and loser returns change over time;
3. In general, the sources of momentum winner and loser returns differ from each other (i.e. winner/loser asymmetry);
4. There is distributional asymmetry for security-level risk;
5. There is distributional symmetry for market-level risk;
6. Momentum winner and loser returns are not generally well explained by linear models on the enhanced momentum variables studied;

### Result 1:

There are specific components that tend to survive over time and be symmetric for winners and losers. In particular, the market value of the market as a whole has a generally positive effect on winner and loser returns, whereas a security's market capitalisation has a generally negative effect. Thus the market's market value has a positive (negative) influence on winner (loser) profitability, and a security's market capitalisation has a negative (positive) influence on winner (loser) profitability. This accords with Asness et al. (2014). They argue against the "myths" that momentum returns are sporadic (myth 1), can only be exploited by shorting losers (myth 2), and that momentum is stronger for small cap stocks than large cap stocks (myth 3). Our findings are that returns to momentum tends to come from winners for small-cap stocks and from (shorting) losers on large-cap stocks (counter to myths 2 and 3), and that the profitable side of momentum depends on the market's market value (counter to myths 1 and 2).

### Result 2:

We find strong support for the theses of Grundy and Martin (2001) and Du and Watkins (2007) – that the sources of momentum profits vary with market state and over time. Our three equal time periods coincide with pre-GFC, GFC and post-GFC periods, and it is clear that market effects dominate during the GFC period, as well as a momentum reversal in the US market. This result calls for further research into momentum profits using techniques that

account for time variation (e.g. survival analysis, Multivariate Adaptive Regression Splines), and/or techniques that involve market state identification (e.g. clustering, Hidden Markov Modelling).

#### Result 3:

In period 1, the ASX200 winners have a strong risk component to their explanation absent from the losers; the S&P500 winners have a strong market-factor explanation whereas the losers are better explained by information availability. In period 2 (which contains the GFC), the ASX200 winners and losers and the S&P500 losers are dominated by market factors, but the returns to S&P500 winners show no influence by market factors and are largely unexplained. In period 3 the ASX200 winner and loser returns and the S&P500 winner returns are poorly explained, and the S&P500 loser return model contains only the market factor component. This winner/loser asymmetry indicates that different sections of the cross-section of returns have different models, and this in turn suggests that machine learning ensemble techniques should be investigated. The methodology employed in this paper can be viewed as an attempt to make a linear ensemble of multiple enhanced momentum hypotheses. Machine learning ensemble techniques seek to create nonlinear ensembles of multiple generated hypotheses, for instance via voting in bootstrap aggregation, weighted voting in Bayesian classification, and recursion in boosting (Dietterich, 2000). Investigation using these techniques is thus a natural extension of the current research.

#### Result 4:

The effects on returns of security-level upside and downside risk are generally asymmetric. This is true between winner and loser models, indicating winner/loser asymmetry, and within models, indicating distributional asymmetry. In period 1, the ASX200 winners show double the exposure to detrimental downside risk than beneficial upside risk, whereas the losers show no exposure to either. Conversely, in period 3, the ASX200 losers show triple the exposure to detrimental upside risk than to beneficial downside risk, whereas the winners show only exposure to detrimental downside risk. The S&P500 winners show exposure only to detrimental downside risk in period 1, and the losers to detrimental upside risk in period 2. The fruitful relaxation of the symmetric distribution assumption for a single regressor indicates that nonparametric methods should be investigated.

#### Result 5:

Unlike security-level risks, the effects on returns of market-level upside and downside risk are generally symmetric. This is true across winner and loser models, indicating winner/loser symmetry, and within models, indicating distributional symmetry. Market level upside and downside risks are generally either present or absent in both winner and loser models, the only exception being the S&P500 in period 2, and are generally both present with similar magnitude, the exception being the S&P500 in period 3. Together, results 4 and 5 indicate that security-level variance is asymmetrical while market-level variance is symmetrical. This has implications for the calculation of security betas which need to be investigated.

#### Result 6:

Returns to losers were almost universally better explained than returns to winners – another form of winner/loser asymmetry - but none of the models explained momentum winner or loser returns well, despite the large number of enhanced momentum ranking variables in the

regressor set. In particular, the information discreteness (ID) of Da et al. (2014) was not selected in any model, and the volume-based continuing overreaction (CO) and turnover ratio (TR) of Byun et al. (2014) and Lee and Swaminathan (2000) made only rare appearances. Information availability, risk, and market factors were the three most prevalent sources of winner and loser returns, but they were generally not prevalent in both winner and loser models at the same time. Semi-strong EMH information was more common in the S&P500 models than the ASX200 models, indicating perhaps that the Australian market was the more informationally efficient over the periods studied. However, the generally low  $R^2$  indicates either that the sources of momentum winner and loser returns remain undiscovered, or that linear models are not the appropriate way to explain them. Furthermore, while several of the successful enhanced momentum anomalies studied by Jacobs (2015) seem to be unrelated to standard momentum, they are still successful strategies, as are other similar strategies not investigated here such as the style momentum of Chan and Docherty (2016). The three implications for future work from result 6 are: firstly, that those enhanced momentum variables which we were not able to include in this paper (analyst forecast dispersion, credit rating, and breadth of ownership) need to be investigated where the current regressor set may have been lacking; secondly, that nonlinear techniques could be profitably employed to produce better models than the linear ones; and thirdly, that further study may be required on winners minus losers anomalies in general, rather than focussing on specific winners minus losers anomalies, such as momentum or the many enhanced momentum variations, in isolation.

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## Conclusions

We found information availability, risk, and market factors to be generally better than past prices, past volumes and semi-strong EMH information at explaining winner and loser returns, but asymmetrically between winner and loser models. We found the use of upper and lower semivariance effective in highlighting both distributional and winner/loser asymmetry. We also found that returns to losers are significantly better explained than returns to winners, but that momentum returns in general are still difficult to explain using linear models. We find even more strongly than Du and Watkins that the momentum anomaly cannot be explained by a single linear model with time invariant regressors. Where the Du and Watkins 2007 result called for the study of the momentum anomaly using time-varying techniques, our findings of winner/loser asymmetry and risk asymmetry calls for an investigation of winners minus losers anomalies in general using nonlinear, nonparametric and ensemble techniques.

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